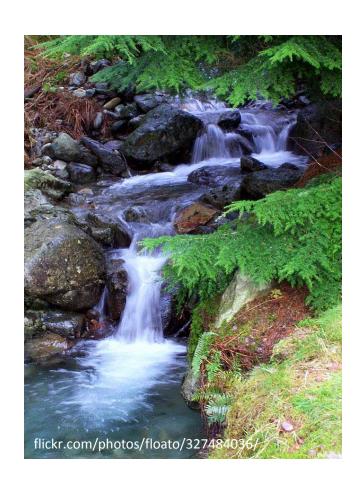
When Green Goes Bad: A Computational Ecology Approach to a Better Understanding of Cyanobacteria, Nutrients, and Lakes

Jeff Hollister, Betty Kreakie, Farnaz Nojavan, and W. Bryan Milstead
Oct 30, 2014



Outline

- Introduction to Safe and Sustainable Water Resources (SSWR) Cyanobacteria Project
- Ecological Modelling of Cyanobacteria
 - Machine Learning Approaches
 - Bayesian Approaches
- The Role of Open Science in our Research
- Recent news N.E. Monitoring (Thanks Hilary Snook!)







Cyanobacteria

- "Bluegreen Algae"
- Photosynthetic bacteria
- Found in fresh and salt water
- Amazing diversity
- Many can fix nitrogen
- Resting spores
- Mobile can harvest nutrients from sediments
- Produce over 80 known toxins





Cyanobacteria Blooms

- Human and Animal Health Risks
- Hypoxia and Fish Kills
- Water Treatment Costs
- Lake Aesthetics –Clarity & Smell
- Quality of Life
 - Recreational Opportunities
 - Property Values
 - Tax Revenues
 - Employment





Cyanobacteria, nutrients, and land use - a nexus for sustainable water resources and human health protection

• **Ecology:** Develop predictive models to relate nutrient loads, land use/land cover, socioeconomic factors, and climate to the frequency, location, and severity of cyanobacterial blooms in lakes of the United States

Contact: Jeff Hollister and Betty Kreakie

 Toxicology: Clarify cyanotoxin effects on mammalian endpoints and exposure biomarker identification for human health risk assessment

Contact: Neil Chernoff

• **Epidemiology:** Characterize cyanotoxin occurrence and nutrient concentrations in US surface waters. Analyses includes assessing risk to human health via multiple exposure scenarios to recreational and drinking waters

Contact: Betsy Hilborn

 Remote Sensing: Describe the retrieval of chlorophyll a concentrations, and water clarity from airborne hyperspectral data and predictions of changes in trophic status in Northeastern Lakes and Reservoirs

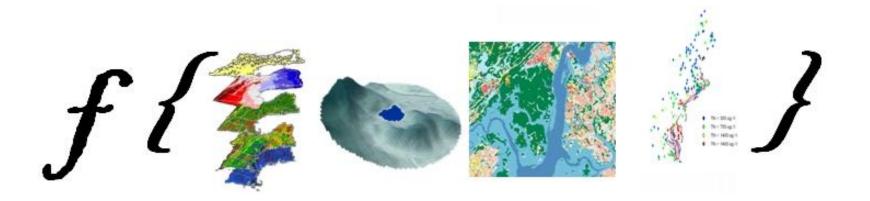
Contact: Darryl Keith

Ecological Modelling





"We are trying to combine what we know from field data, what we know from modeled data, and what we (think) we know about cyanobacteria and create predictive models of the probability of bloom events."





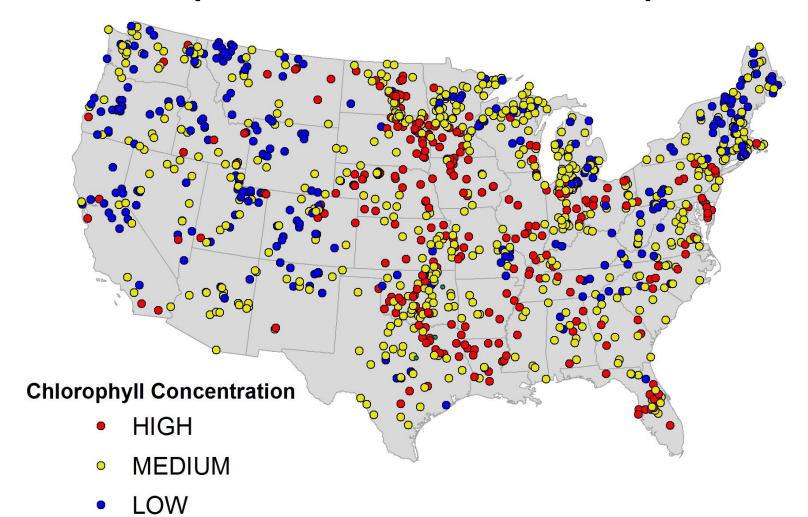
National Lake Assessment (NLA)

- Spatially balanced, probabilistic sample of 1000+ lakes
- Developed to provide inference on the condition of the lakes in the contiguous United States at the national and ecoregional level
- Includes freshwater lakes greater than 4 hectares (excluding Great Lakes and Great Salt Lake) and deeper than 1 meter
- First Survey in 2007; Second in 2012, Third planned for 2017.



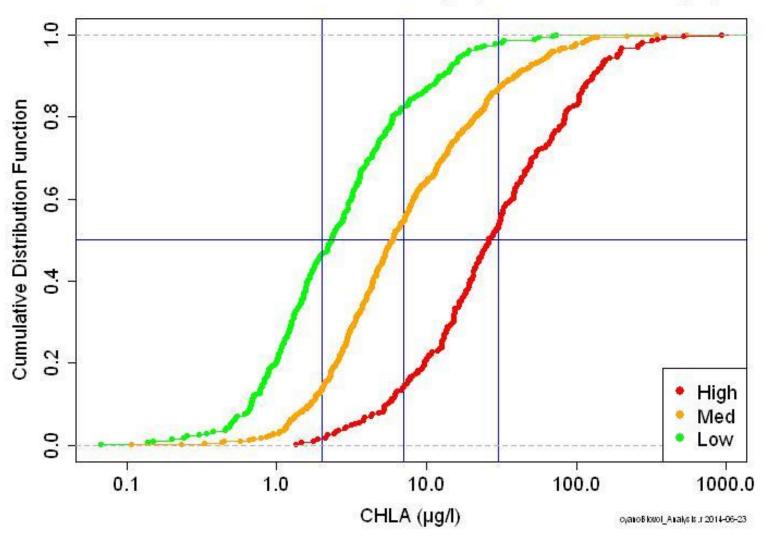


Map of 2007 NLA Samples





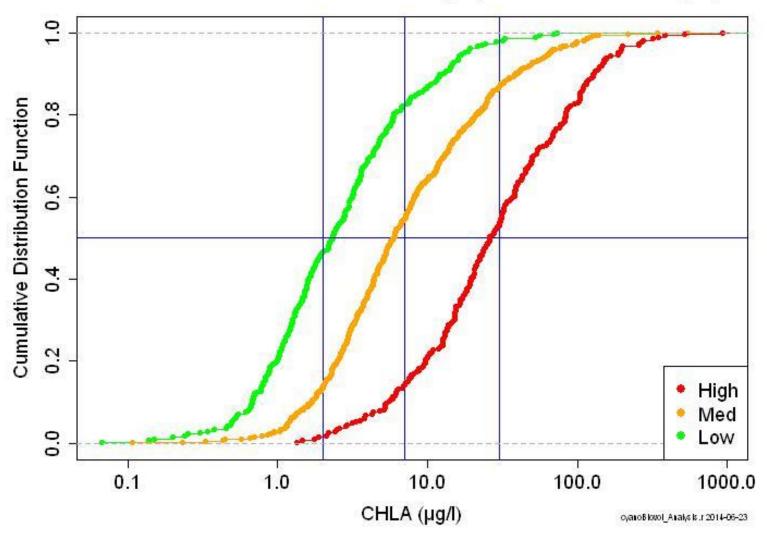
Cummulative Distribution Function by Cyano Biovolume Category



Biovolumes from Lester Yuan (EPA OW) and Beaulieu et al. 2013. Nutrients and water temperature are significant predictors of cyanobacterial biomass in a 1147 lakes dataset. L&O 58:1736-1746.



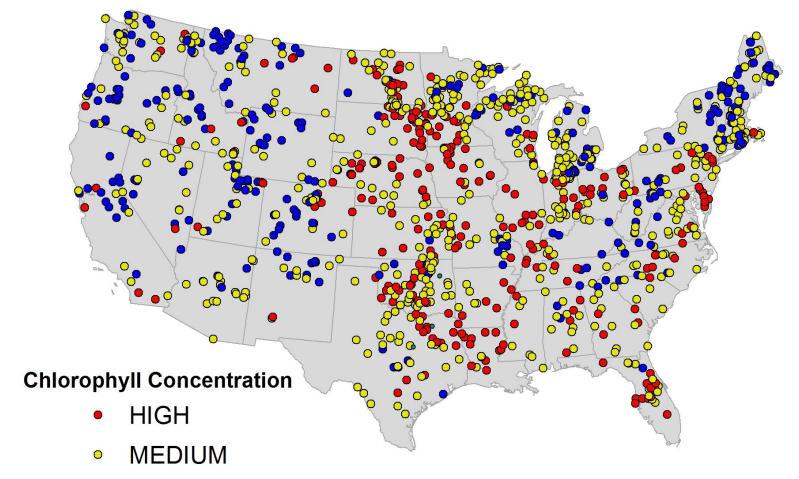
Cummulative Distribution Function by Cyano Biovolume Category



Assumption: We can use *Chl a* as a proxy for cyanobacteria biomass & ...



Map of 2007 NLA Samples



LOW

How Can We Predict Chl a Class?

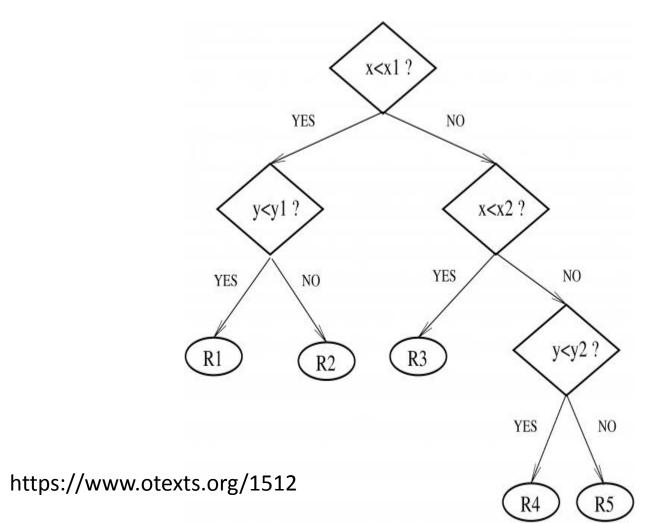


Random Forest:

Definition 1.1. A random forest is a classifier consisting of a collection of tree-structured classifiers $\{h(x, \Theta_k), k = 1,...\}$ where the $\{\Theta_k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x.



CART Model: Classification and Regression Trees





Random Forest

- Can throw any kind of data at it
 - Included highly correlated variables and NAs
- Can not over fit
 - No weird pruning rules
- Measures of variable importance
- Model verification build directly into the algorithm
- Computationally fast and easy to code
 - Even with very large data sets



Summary of Random Forest

- Select training data (~2/3) with replacement for each tree
- Randomly select subset of variables
 - Actually done for each split
- Make a tree
- Record Out-Of-Bag (OOB) errors
- Permute variables
- Record altered OOB
- Repeat 10,000 times

**Each tree votes for a classification



Random Forest Analysis

Response Variable

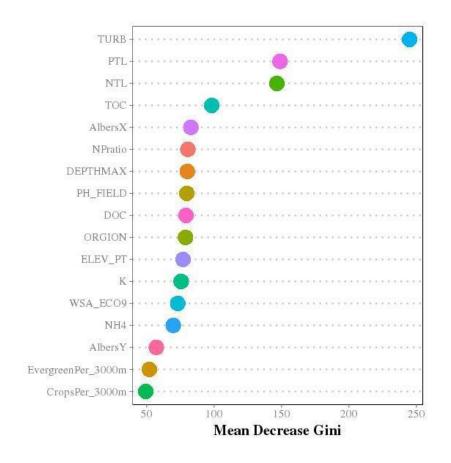
Chlorophyll a Category

Predictor Variables (WQ)

- Geographic (5)
- Morphometry (14)
- NLCD 3km (17)
- Water Quality (34)
- Other (2)



Random Forest Analysis Selected WQ Predictors



Out of Bag Error Rate: 21%



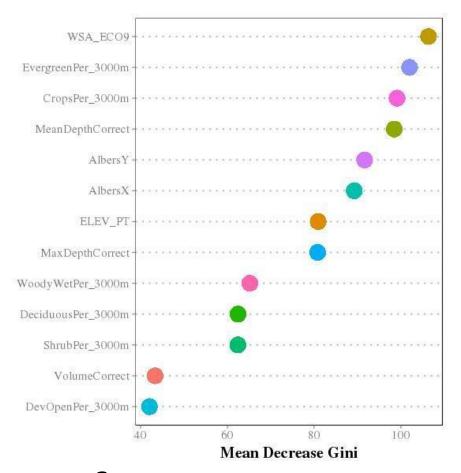
Random Forest Analysis

 Water quality data difficult/expensive to obtain

 What if we just use the GIS ready predictors to assign Chl a category?



Random Forest Analysis Selected GIS Predictors



Out of Bag Error Rate: 32%



Random Forest Modelling

WQ Predictors

VARIABLE	PERCENT
K	1.00
NPratio	1.00
NTL	1.00
PTL	1.00
тос	1.00
TURB	1.00
WSA_ECO9	1.00
ORGION	0.46
DOC	0.21
DEPTHMAX	0.06

GIS Predictors

VARIABLE	PERCENT
AlbersX	1.00
CropsPer_3000m	1.00
EvergreenPer_3000m	1.00
WSA_ECO9	1.00
MeanDepthCorrect	0.99
AlbersY	0.40
ELEV_PT	0.04
MaxDepthCorrect	0.01

OOB Error Rate: 32%

OOB Error Rate: 21%



Future Modelling Efforts

- Explore temporal dynamics and phytoplankton community turnover using a long-term regional data set
- Bayesian forecasting of predicted cyanobacteria bloom risk for lakes in the continental United States
- Develop regional models based on citizen science data (e.g. URI Watershed Watch Data)



Water Quality Modeling Approaches

- <u>Process-based models</u>, Deductive reasoning
 - Conceptually dividing a system into subsystems
 - Equations are derived based on existing knowledge and general laws of physics
 - Solving equations for all subsystems together
 - Box-and-arrow charts plus differential equations

- <u>Statistical models</u>, Inductive reasoning
 - Statistical models are mostly driven by data
 - Data often limited to a specific region (local or subregion)
 - We usually don't combine subsystem models
 - Statistical modeling often does not incorporate existing knowledge – we reinvent the wheel every time we have a new data set.



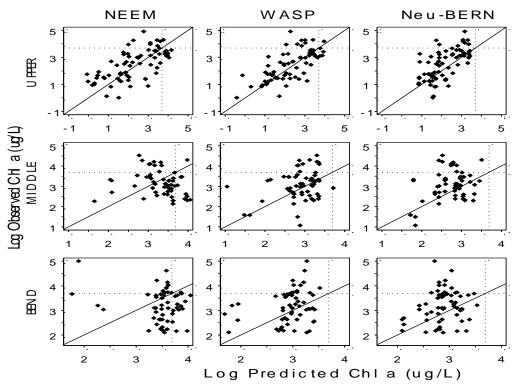
Model Updating

Adaptive Management

- Continuous observation of the ecosystem to gauge the impact of policies and management actions
- Communicating the ecosystem's status with policy makers and managers
- Updating the management actions and recommendation



High Prediction Uncertainty



Stow et al., 2003, Comparison of Estuarine Water Quality Models for Total Maximum Daily Load
Development in Neuse River Estuary



Quantifying Uncertainty

Sources of Uncertainty

- Natural ecosystem variability
- Current knowledge of environmental processes
- Model structure uncertainty
- Data and observation (e.g., observation error, missing data)
- Computational restrictions



Other Considerations

- Small/incomplete data set accommodation
- Visual interface Communication



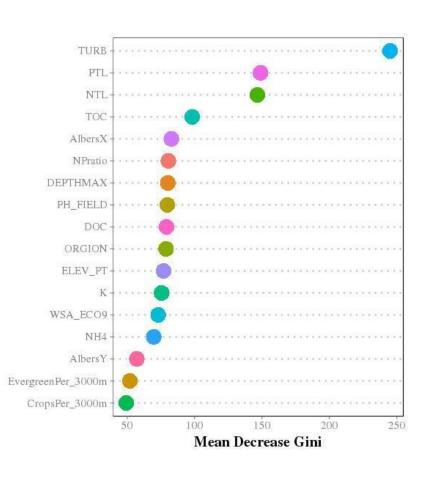
Network-based Bayesian Model

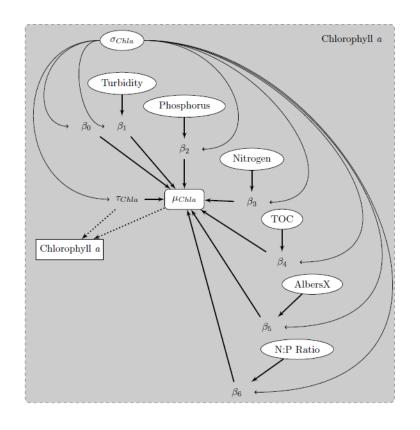
Model Formulation

- Establishing cause-effect diagram using biological/ecological knowledge (box-andarrow charts)
- Quantifying the links
- Model updating



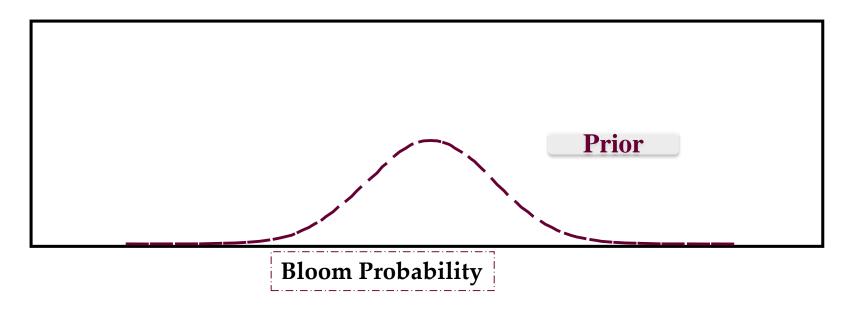
Proposed Network-based Bayesian Model







Model Evaluation & Updating



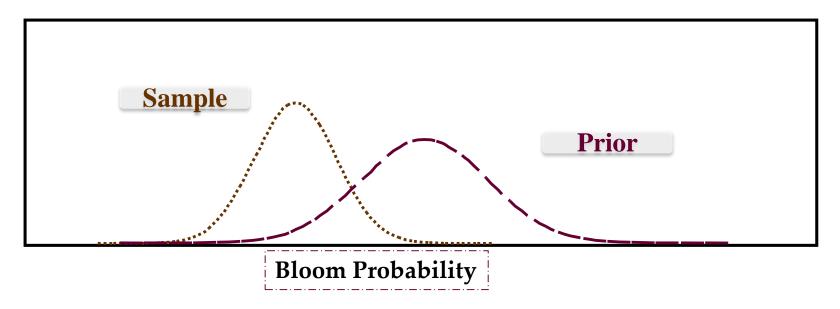
• Prior: 2007 NLA data set

Likelihood: 2012 NLA data set



Model Evaluation & Updating

Prior ⊗ Likelihood

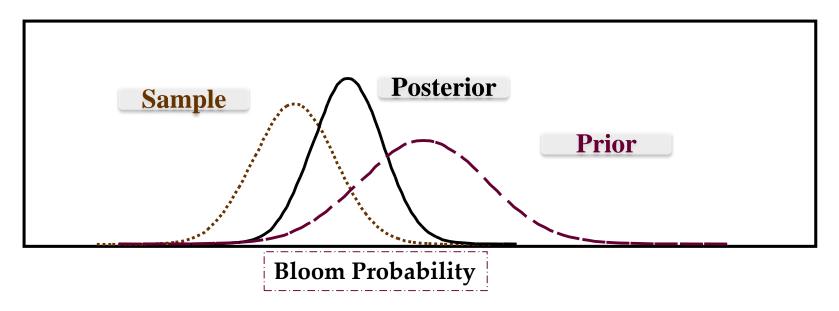


- Prior: 2007 NLA data set
- Likelihood: 2012 NLA data set



Model Evaluation & Updating

Posterior ∝ Prior ⊗ Likelihood



- Prior: 2007 NLA data set
- Likelihood: 2012 NLA data set

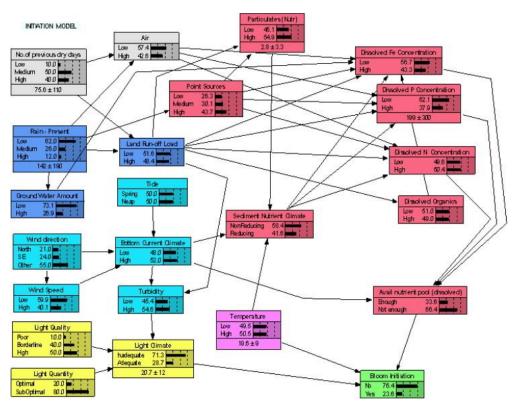


Benefit of Network-based Modeling

- Comprehensive summarizing all available information
- Flexibility both empirical models and mechanistic models can be part of a network model
- Updating over space and time
- A starting point no need to wait for all necessary information



Previous Applications (1)



Johnson et al., 2010, An Integrated Bayesian Network approach to *Lyngbya majuscula* bloom initiation



Previous Applications (2)

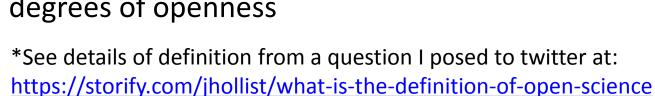
Using the observational data sampled during the growing season in 2007–2011, a Bayesian hurdle Poisson model was developed to predict cyanobacteria abundance in lake Paldang, South Korea.





What is Open Science?

- Many Flavors
- But many agree on:
 - Openness and transparency
 - free access to code, data, publications
 - repeatable
 - reusable
 - web enabled
 - degrees of openness







- Expected and/or required
 - Increasing Access to the Results of Federally Funded Scientific Research
 - John Holdren, Director, White House OSTP
 - Feb 2013
 - NSF
 - Publishers
 - #PLOSfail/#PLOSwin
 - Carly Strasser at DATA PUB



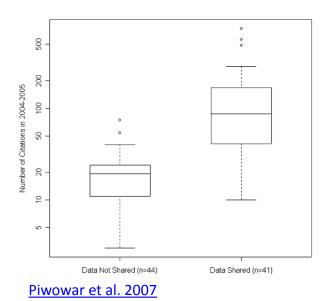






Benefits

- Open Data = More citations (Piwowar et al. 2007)
- Up-to-date statistics on readership (e.g PLOS ALM)
- Accelerates research and discoveries (e.g. <u>Woelfle et al.</u>
 2011)





ImpactStory Metrics



- It keeps us honest
- Prevents this:





- Hot off the press:
 - Weecology Blog: <u>"Sharing in Science: my full reply</u> to Eli Kintisch"
 - Living in an Ivory Basement: <u>"Thoughts on open science my response to Eli Kintisch"</u>
 - Science Careers Article by Eli Kintisch: Give, and It
 Will Be Given to You



Open Science and Our research

Open Access

Open Source

Open Data

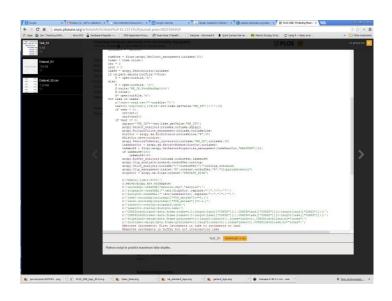


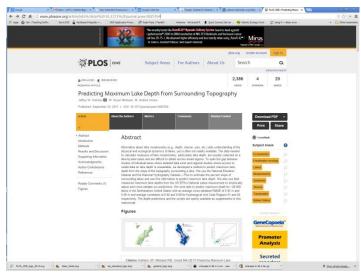


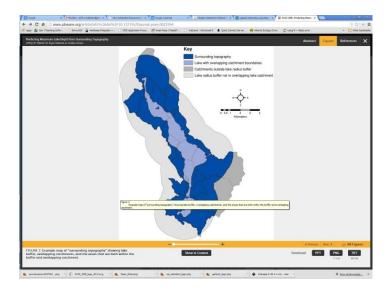


Open Access: What we've done

- Hollister et al, 2011
- Hilborn et al, 2013
- Milstead et al, 2013









Open Access: What's next?

- Goal: All publications open access
 - Journal choice (e.g. PeerJ, F1000Research, eLife, Frontiers In, etc.)
 - Funds to pay for OA charges in traditional journals









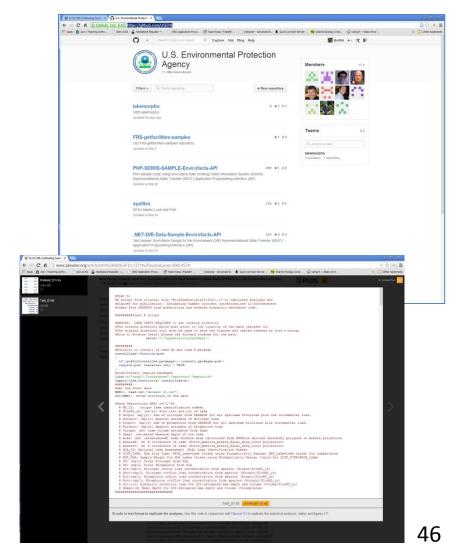


Open Source: What we've done?

- Use Open Source
 - R, Python
- Supplemental Information
- Github









Open Source: What Next

- Continued use of Github
 - R packages
 - manuscripts (e.g., Ram, 2013)
 - posters/presentations (e.g., okbroman)
- Working with the community
 - Software Carpentry
 - Other groups

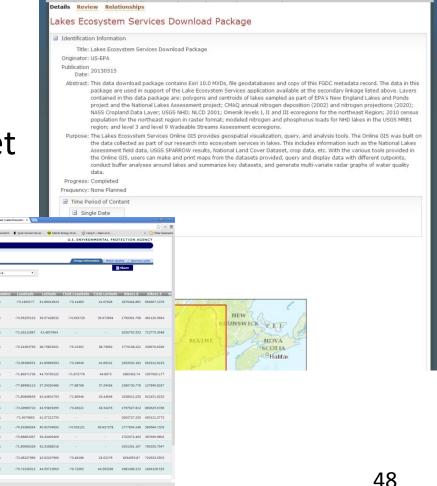






Open Data: What we've done

- Supplemental Info
- Portals
 - EPA Environmental Dataset Gateway
 - APEX/Oracle



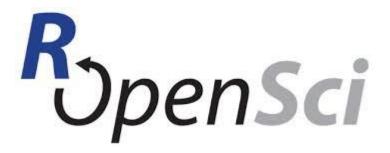
⇔EPA Environmental Dataset Gateway (EDG) BROWSE DATA REUSE RESOURCES



Open Data: What's Next

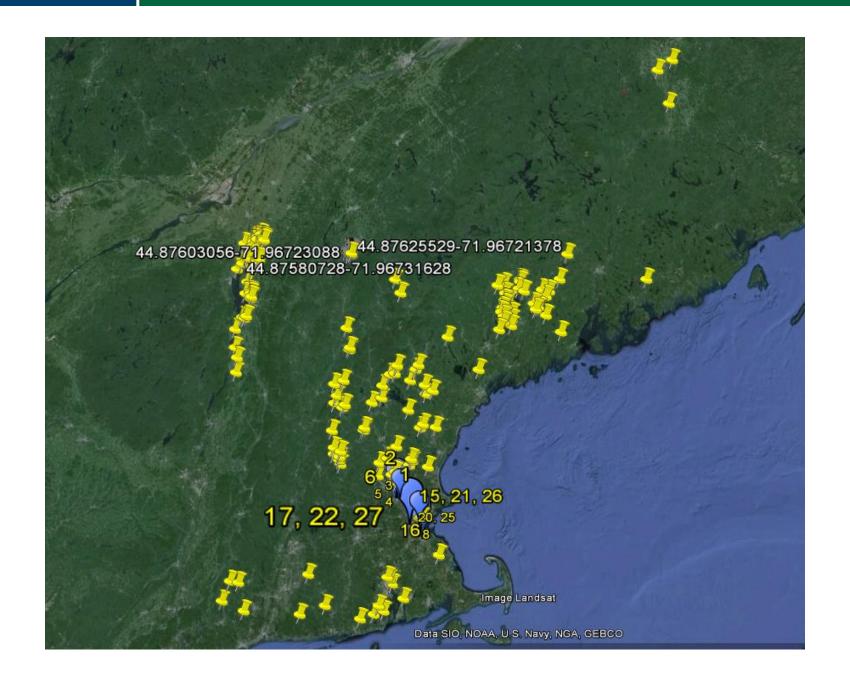
- Linked Open Data
- Web APIs
 - Use HTTP
 - GET, POST, PUT, etc.
 - Access data
 - Programmatically
 - Machine-to-machine
 - rOpenSci: great example



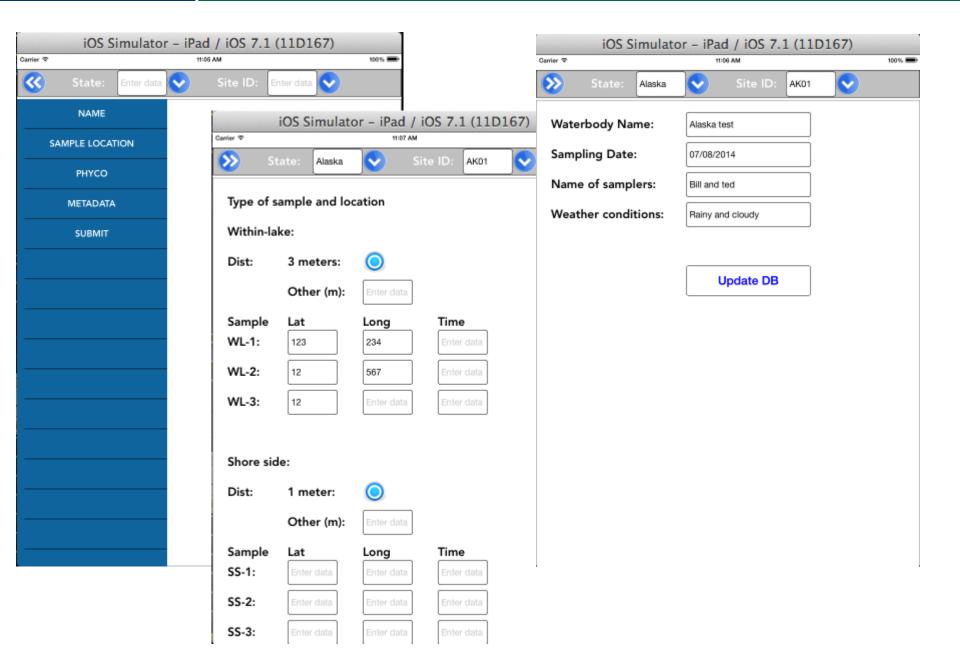








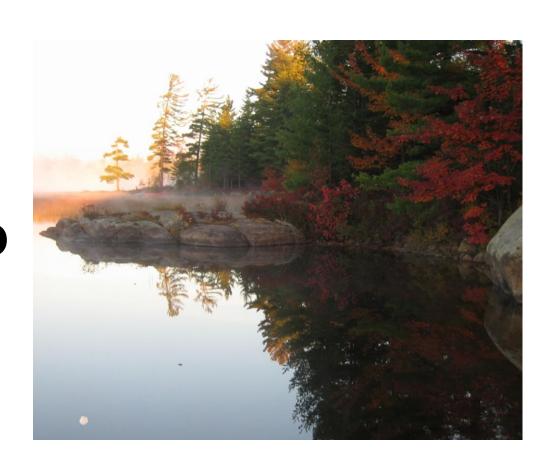






Thank you!

Questions?



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